Cross-Platform Machine Learning Characterization for Task Allocation in IoT Ecosystems

Wanlin Cui Yeseong Kim Tajana S. Rosing
University of California San Diego
{w8cui, yek048, tajana}@ucsd.edu

Abstract— **With the emergence of the Internet of Things (IoT) and Big Data era, many applications are expected to assimilate a large amount of data collected from environment to extract useful information. However, how heterogeneous computing devices of IoT ecosystems can execute the data processing procedures has not been clearly explored. In this paper, we propose a framework which characterizes energy and performance requirements of the data processing applications across heterogeneous devices, from a server in the cloud and a resource-constrained gateway at edge. We focus on diverse machine learning algorithms which are key procedures for handling the large amount of IoT data. We build analytic models which automatically identify the relationship between requirements and data in a statistical way. The proposed framework also considers network communication cost and increasing processing demand. We evaluate the proposed framework on two heterogenous devices, a Raspberry Pi and a commercial Intel server. We show that the identified models can accurately estimate performance and energy requirements with less than error of 4.8% for both platforms. Based on the models, we also evaluate whether the resource-constrained gateway can process the data more efficiently than the server in the cloud. The results present that the less-powerful device can achieve better energy and performance efficiency for more than 50% of machine learning algorithms.**

I. INTRODUCTION

The emerging Internet of Things (IoT) applications involve many data-driven and information retrieving procedures to efficiently serve Big Data [1]. As evidenced by the appearance of industrial IoT gateways and microprocessors specialized for IoT workloads, IoT systems present more complex device hierarchy including new computing nodes, e.g. wearables and smarter gateways [2,3,4]. Traditionally, a system candidate widely assumed to perform the data processing procedures is parallel system architectures on clouds which mask the computation burden by taking advantage of multiple powerful processors [5]. However, the assumption is facing many challenging issues such as security, quick and reliable response in unreliable and constrained network conditions [6]. In this context, *fog computing*, also known as edge computing, has been considered as an alternative solution to decentralize the application services into different places which the data are produced [7]. For example, a gateway enhanced with processing capability could also execute a wide range of machine learning algorithms instead of transferring large data for the cloud computing [2].

An important research question related to this new view of the IoT device hierarchy is how to determine and balance the data processing workload across completely different IoT devices, e.g., powerful servers vs. gateway devices. Some research has investigated how to allocate tasks across either similar platforms, e.g., task migration in data centers [10, 11] or different architectures for specific tasks, e.g., mobile computation offloading [12]. In the context of the IoT and Big Data, we further need to explicitly quantify the performance and energy requirement of emerging data processing applications and machine learnings. Thus, it is essential to model the application behaviors across the heterogenous IoT devices. In addition, the modeling procedure should be automated to cover the increasing number of IoT applications.

In this paper, we propose a novel cross-architecture data processing application characterization framework, called CrossTest, which examines and quantifies energy and performance requirements of diverse applications, when heterogeneous devices of the IoT hierarchy communicate with each other to transfer data of various sizes. To this end, our framework first builds cross-platform models which predict the requirement of the applications with the consideration of the data size. To cover diverse data processing applications of IoT, the proposed model generation is completely automated and do not require any prior knowledge of the characterized applications. In addition, the models are carefully generated to avoid under- and overfitting issues so that they accurately identify resource demands of the future data processing in the Big Data domain. The proposed framework also investigates how the network bandwidths affect system resource usage of the data communication between a server in the cloud and a gateway device at the edge. Based on the identified models for the application requirements and the network communication costs, we perform a what-if analysis which verifies whether a gateway device can execute diverse data processing applications more efficiently, in terms of energy and performance, than the server platform.

We evaluate our framework with Raspberry Pi and Intel SR1560SF server, in which they represent two state-of-the-art heterogeneous devices, a resource-constrained gateway and a commercial server platform, respectively. In this work, we focus on machine learning (ML) algorithms which are the common key parts of IoT data processing applications. We show that the proposed models can accurately estimate the performance and energy consumption of the applications which perform ML algorithms, with less than error of 4.8% for both the two platforms. We also show a practical value of the

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generated models by addressing a task allocation problem of IoT ecosystems, i.e., where to execute a data processing application between a gateway device and a powerful server. In the evaluation, we present that more than 50% of ML algorithms can be executed on a resource constrained device with better energy and performance efficiency.

II. RELATED WORK

A swarm of IoT devices is expected to produce a large amount of data than ever before more than 2000 terabytes [1]. To efficiently provide up-to-date information and better quality of the service by assimilating the Big Data, the IoT ecosystems should mitigate computation burden of clouds by performing a part of application tasks at edge [8]. Many applications have been actively developed across heterogeneous computing devices, from embedded systems to high-performance systems using diverse machine learning algorithms, such as information identification [2,3] and context recognition [9].

To understand impact of the data processing algorithms, earlier researchers have characterized resource usage of various IoT applications for different system platforms. For example, Magalhães et al. [10] modeled resource usage of real-world applications such as browsing and bidding on clouds platforms. Lee et al. [11] directly focused on the key procure of the IoT applications for power efficiency of large-scale systems. Kliazovich et al. [23] presented a workload distribution simulator which estimates energy consumption of components in data centers including servers and switches. Recent research has also focused on workload characterizations on resource-constrained devices, e.g., gateways [2], since the less-powerful computing devices would be closer to raw sensory data produced by small IoT devices and thus able to process them in a more efficient way than the servers. For example, Carbajales et al. [13] investigated the power requirement of data sensing on Raspberry Pi as a representation of a small device. Lane et al. [14] characterized neural network algorithms for various embedded devices including wearables and smartphones. Bellagente et al. [15] examined the feasibility of typical tasks of gateways on state-of-the-art embedded systems.

Such research efforts have focused on a specific application and similar computing devices. However, the IoT ecosystems are expected to include diverse computing nodes of completely different architectures. Thus, workload characteristics should be understood in notion of IoT ecosystem hierarchy. We focus on the cross-platform characterization of IoT data processing workloads, in particular, a wide range of machine learning algorithms.

III. AUTOMATED CHARACTERIZATION OF MACHINE LEARNING ALGORITHMS

A. Measurement Setup

We consider two heterogeneous device platform candidates in the IoT computing node which exhibit significantly different computing power: a gateway-level device and a server. In literature [2,7], gateway-level devices may collect raw sensory data from other IoT devices, e.g., smartphone and wearables, and process them internally if required. As a counterpart, centralized server platforms in the cloud can also process ML algorithms [1, 12] once the collected raw sensory data are transferred. Figure 1 shows our measurement setup which identifies the system requirements of the two target platforms. For the representation of a resource-constrained device, we use Raspberry Pi 2 running with Linux systems which can also serve typical tasks of gateways [2]. For the representation of the powerful server platforms, a commercial Intel SR1560SF server is used. The detailed specifications of the two devices are summarized in Table 1. The two devices use different instruction set architectures (ISA), i.e., x86 and ARM. In the rest of the paper, we call the two devices as *Gateway* and *Server*, in short.

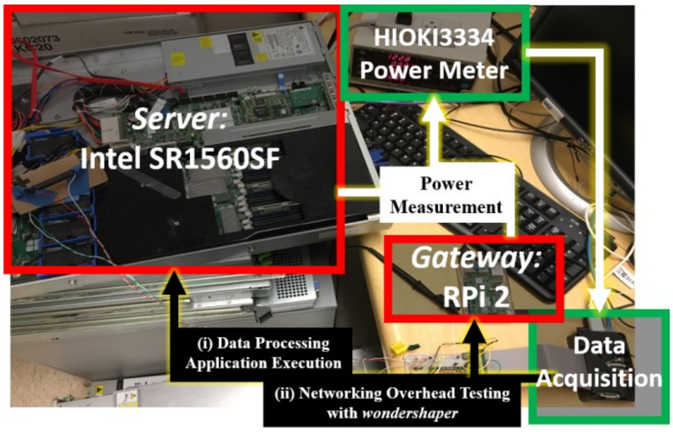


Figure 1. Measurement Setup

We execute diverse data processing applications, 22 in total, on both devices as labeled with (i) in Figure 1. A wide range of machine learning algorithms, which perform classification, clustering, and regression tasks, are used as representatives of the data processing applications. Table 2 shows the list of experimented machine learning algorithms. For architectural compatibility of applications, the algorithms are implemented with Python 2.7 using scikit-learn library [16]. We also evaluate requirements of network communication of the Gateway, as labeled with (ii) in Figure 1, to understand how much additional network cost is required in the resource-constrained device. We use a microbenchmark that generates network packets while the network bandwidth is controlled by *wondershaper* tool. The RPi can transfer data by up to 40Mbps and 100 Mbps of bandwidths for WiFi and Ethernet, respectively. While executing each algorithm and network communications, we also measured the machine power consumption of the two platforms using HIOKI 3334 power meter [19].

Table 1. Evaluated Computing Nodes

Type	Specification
Gateway at edge: Raspberry Pi 2	ARMv7 Cortex A7 processor (4 cores, 900MHz) DRAM size: 1GB Ethernet: SMSC LAN9514 10/100 Controller WiFi: Edimax EW-7811Un 802.n Adapter
Server in cloud: Intel SR1560SF	Intel Xeon E5440 processor (8 cores @ 2.83GHz) DRAM size: 8GB

Table 2. Evaluated Machine Learning Algorithms

Types	Machine learning algorithms (22 in total)
Classification	*AdaBoost, Decision Tree (DTree), Random Forest (Forest), kNN (Nearest Neighbors), Naïve Bayes (Bayes), Linear-SVM, Poly-SVM, Exp-SVM*
Clustering	*Affinity Propagation (Affinity), Birch, DBSCAN, K-Means, Mean Shift, Spectral, Ward*
Regression	*Bayesian, Elastic Net, Lasso, LARS Lasso, Linear Regression, Ridge*

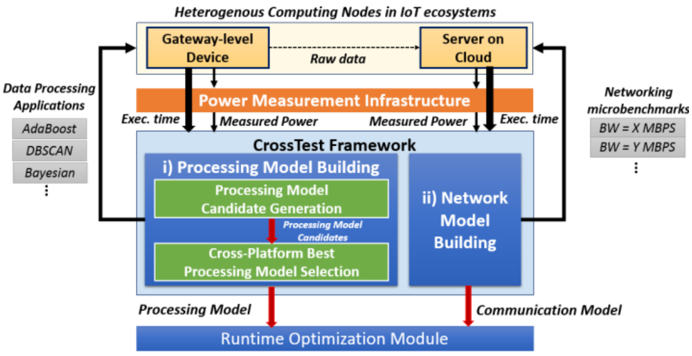


Figure 2. Overview of CrossTest

B. *Overview of CrossTest*

Figure 2 illustrates an overview of the proposed CrossTest framework. It characterizes cross-platform energy and performance requirements for data processing applications with consideration of network communications in an automated way. The characterization stage has two modules, i) *processing model building* and ii) *network model building* module. Each module builds a *processing model* and a *network model*, respectively.

The *processing model building* module characterizes resource usage behavior of data processing applications. It executes an application on each machine by increasing the size of the processed raw data. Different data processing applications have different underlying trends between the processed data size and the requirement of either energy or performance, e.g., linear vs. polynomial relationship. Thus, a key technical challenge is how to identify the appropriate relationship for each application. This module solves this issue through two steps: processing model candidate generation and cross-platform best processing model selection. In the processing model candidate generation step, the CrossTest builds multiple models for the heterogenous platforms, called *processing model candidates*, where each of them is constructed based on different regression models, e.g., a linear and an exponential model. Then, in the cross-platform best processing model selection step, for the generated model candidates, it chooses the best model, called *processing model*, which accurately describes the dependency between the data size and the requirement of energy and performance without under- and overestimation. Based on a set of statistical analysis, the model generation and selection procedures are completely automated.

The *network model building* module characterizes the power requirements for network speeds of different network communication mediums, e.g., Ethernet and WiFi. This module executes a microbenchmark which transfers data from the gateway device to the server while varying network bandwidths. Based on the power consumption collected for the microbenchmark, it builds a regression-based model, called *communication model*, which estimates the power consumption for different bandwidths of each network medium.

The *processing model* of each data processing application for heterogeneous platforms and the *communication model* are stored into the *runtime optimization module*. This module can utilize the generated models to solve diverse system management problems, e.g., task allocations. In the following subsections, we discuss the two key modules, the *processing model candidate building* and *network model building* module. We also discuss how the models can be used to solve runtime optimization problems for task allocations in Section IV.C.

C. *Processing Model Building*

1) Energy and Performance Characteristics for Data Sizes

To understand how applications performing ML algorithms behave on different platforms, we measured energy and performance on the *Gateway* and *Server*. Figure 4 shows the measurement results for two representative algorithms, *kNN* and *birch*. In this analysis, we got the following key findings.

Strong energy/performance relationship for data size. Each algorithm exhibits a strong relationship between the raw data size and the energy/performance requirement. For example, the *kNN* algorithm has a strong linear relationship (Figure 3a), and the *birch* algorithm has a very strong relationship of a polynomial (Figure 3b). The strong relationships are observed for all 22 tested algorithms.

The requirement relationships for the data size are related to algorithm computation complexities. For example, the linearity of the *kNN* algorithm is directly explained by its complexity, $O(n)$ [20]. If the complexity only depends on the data size, we may model the application behavior by choosing a regression model which has the same degree to the complexity. However, there are other ML algorithms whose theoretical complexities are explained with more parameters determined through actual algorithm executions. For these algorithms, we need to identify the dependency through analysis of actual system behaviors. For example, the complexity of the Lloyd's method, which implements *k-Means*, is $O(ni)$ where i is the number of clustering iterations needed to decide k clusters which sufficiently minimize inter-cluster variations [21]. In our measurement, since a larger data size generally requires more iterations, i is linearly proportional to the data size, resulting in the complexity of $O(n^2)$ for the actual program execution. In these cases, the theoretical complexity only gives implicit information for the dependency. To cover diverse applications and algorithms without loss of generality, the CrossTest automatically extracts their dependencies from the behaviors of energy and performance collected by the actual measurement, instead of manually checking the algorithm time complexity.

Asymmetric energy/performance behavior across machines. Due to computing power differences, energy and performance requirements significantly vary across the two platforms. For example, as also shown in Figure 3, the

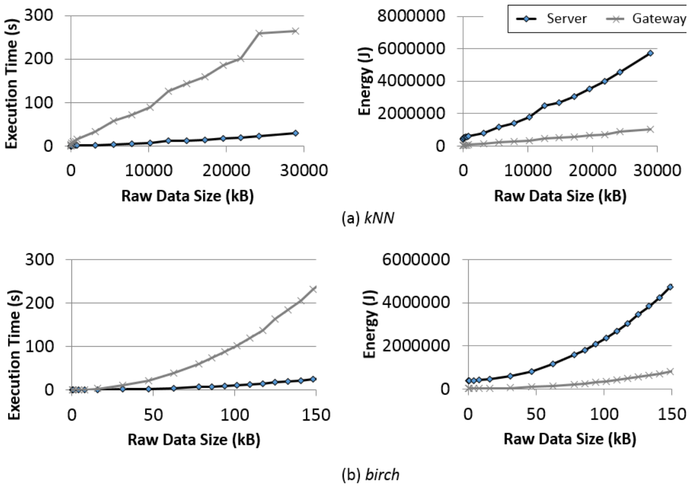


Figure 3. Energy and Execution Time Behaviors for *kNN* and *birch* algorithms

algorithm execution time of the *Gateway* is much slower than the *Server*. However, since the *Gateway* uses a low-power ARM processor, the required energy consumption is significantly smaller. Thus, for some scenarios, the *Gateway* may perform data processing tasks more efficiently than the *Server*. This strategy can also reduce tremendous task amount in the centralized cloud systems and the cost of additional network communications. For example, if an IoT application is delay-tolerant, to achieve better energy efficiency, we could perform the computation at the edge devices. In addition, for relatively small data, we can process them on the resource constrained device to save energy at the expense of small performance degradation. Moreover, when the network is unreliable, the gateways can provide better response time to the IoT actuator devices than the server platforms.

2) Processing Model Candatate Generation

In the first model candidate generation step, the CrossTest generates multiple models, i.e., *processing model candidates*, which identify the relationship between the data size and the energy/performance requirements using different regression models. For each algorithm α running on a platform P, we denote the models of the energy and execution time by $e_P^\alpha(s)$ and $t_P^\alpha(s)$, respectively, where s is the data size. In our current implementation, the CrossTest utilizes four regression models which can be solved by the method of least squares: linear, polynomial, log, and exponential regression. More formally, *processing model candidates* are defined by four sets, $\mathcal{M}_{linear}, \mathcal{M}_{poly}, \mathcal{M}_{log}$, and $\mathcal{M}_{exp}$ where each set corresponds to each regression model. Each individual set includes following four cross-platform models for the combination of a device type (*Gateway*/*Server*) and a requirement (energy/execution time):

$$\{e_{Gateway}^\alpha(s), t_{Gateway}^\alpha(s), e_{Server}^\alpha(s), t_{Server}^\alpha(s)\}.$$

3) Cross-Platform Best Processing Model Selection

Figure 4a shows an example for generated models of the four processing model candidates. The models estimate the energy consumption of the *Server* for *AdaBoost* classification algorithm. This example shows that a measured energy exhibits

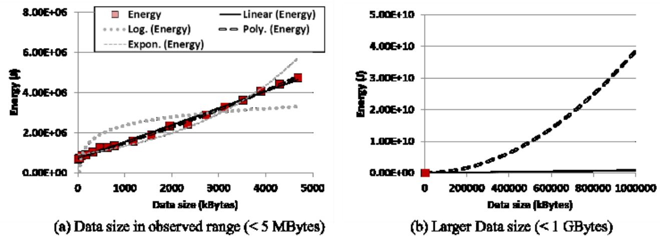


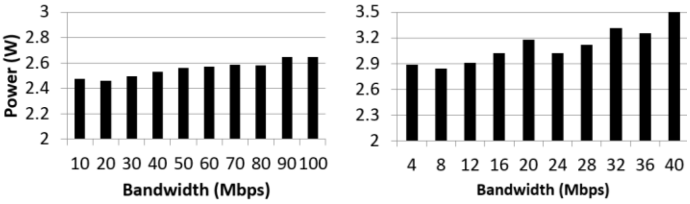
Figure 4. Regression Candidates for Energy Model of *Adaboost* for Intel SR1560SF (*Server*)

a strong linear relationship, while four models have different levels of accuracy.

One naïve way to choose a best model set among the four model sets is to use the estimation error for energy/execution times. However, it may select an overfitted model. The bias model may yield reasonable prediction results for the observed data size range, e.g., characterized data sizes, but would give significantly inaccurate results for large data sizes of the IoT domain. For example, as shown in Figure 4a, the predictions of both linear and polynomial models seem to be accurate. However, if we consider larger data sizes as shown in Figure 4b, the polynomial model (dotted line) completely loses the linearity (solid line) which is observed in the measurement.

We address the bias issue using a cross validation procedure [17]. The key insight of the procedure is that, if a regression model is unbiased, the error should be small even when the model is built only using partial measurement results. For example, let assume that an ML algorithm has a quadratic relationship and both a polynomial model $f_{Poly}(s)$ and a linear model $f_{Linear}(s)$ trained with all measurement results present low error. Let also consider another linear model, $f'_{Linear}(s)$, which is built by excluding measurement results for a middle range of the data size. Then, $f'_{Linear}(s)$ is more likely to lose the accuracy for the middle-range data, compared to $f_{Poly}(s)$.

The CrossTest implements this idea using 3-fold cross validation. Let define a vector of measurement results, $R = \langle(s_1, y_1), (s_2, y_2), \ldots, (s_N, y_N)\rangle$ where s_i is the raw data size and y_i is the measured object value of either the energy or execution time. R is sequentially divided by 3 sub vectors, R_1, R_2, and R_3 so that each sub vector has almost equal lengths, i.e., $R_1 = \langle(s_1, y_1), \ldots, (s_{\lfloor N/3 \rfloor}, y_{\lfloor N/3 \rfloor})\rangle$. Then, each regression model can be regenerated with R_1 and R_2, and the accuracy of the regenerated model is validated with R_3 in MSE (Mean Squared Error). This procedure is repeated for the other sub vector combinations, (R_1, R_3) and (R_2, R_3), yielding two more MSE values. The cross-validated MSE values are more durable to the bias issue than the error of the original model which assumes complete knowledge of the measurements. We compute the average MSE value for the models in each candidate set, and then choose the best set $\widehat{M}$, whose cross-validated error is minimum, among $\mathcal{M}_{linear}, \mathcal{M}_{poly}, \mathcal{M}_{log}$, and $\mathcal{M}_{exp}$. The models of the best set are stored to the runtime optimization module as the processing models of the algorithm. In Section IV.A, we discuss which models are selected for the ML algorithms, and evaluate the estimation accuracy of the models.



(a) Ethernet (b) WiFi

Figure 5. Average Power Consumption of Two Network Types of Raspberry Pi 2 (*Gateway*)

D. Network Model Building

The other important factor which affects the resource usage is the network communication cost. To show how the cost is changed for various network conditions of IoT ecosystems, Figure 5 presents average power consumption for the bandwidths. Since IoT gateways may use a wireless technology as well as the conventional wired connection, we evaluate two representative network components, Ethernet and WiFi. For the two communication mediums, we observed that the dynamic power cost to transfer data linearly grows with an increase of the bandwidths. This observation also agrees with the findings of other embedded devices [22]. The static power is relatively higher than the dynamic power, e.g., at least 2.4W and 2.8W for Ethernet and WiFi case respectively. The tested network environment was very reliable in our evaluation setup, thus Ethernet and WiFi can serve up to 100Mbps and 40Mbps of bandwidths, respectively. There was minimal network contention and the used WiFi router was installed within a few meters. Thus, in case of more challenging network condition, the bandwidth could be limited more significantly.

The *network model building* module exploits a linear regression to build the *network model*. The model estimates a power level of a given bandwidth (BW) for each network medium. We denote the network models for Ethernet and Wifi, as $N^{ETH}(\mathrm{BW})$ and $N^{WIFI}(\mathrm{BW})$, respectively. The power modeling of other possible communication mediums, e.g., BlueTooth and GSM, is out of scope in this work. However, the automated modeling technique of the CrossTest could also build the network model for other network mediums with minimal changes. The generated network models are also stored in the runtime optimization module. In Section IV.C, we discuss how the constructed processing models and the network models can be used for diverse task optimization problems.

IV. EXPERIMENTAL RESULTS

A. Experimental Setup

We implement the CrossTest using Python 2.7 and Scikit-learn 0.17.1 library [16] for statistical analysis. All results are evaluated using the same measurement setting described in Section III.A. We collected energy consumption and execution times of each algorithm for the data sizes which can be executed within 5 minutes. We empirically set this timeout so that energy/performance relationships for the data size are sufficiently observed over all the 22 ML algorithms. For example, with the timeout of 5 minutes, we could test *kNN* algorithm with a range from 100 to 80 million data points, and

Table 3. Modeling Methodology selected by CrossTest

Classification		Clustering		Regression	
AdaBoost	Linear	*Affinity*	Poly	*Bayesian*	Poly
Decision Tree	Linear	*Average Linkage*	Poly	*Elastic Net*	Poly
Random Forest	Poly	*Birch*	Poly	*Lasso*	Poly
K Nearest Neighbor	Linear	*DBScan*	Poly	*LARS Lasso*	Poly
Linear SVM	Poly	*K Mean*	Poly	*Linear*	Linear
Naïve Bayes	Linear	*Mean Shift*	Poly	*Ridge*	Poly
Polynomial SVM	Poly	*Spectral*	Poly		
RBF SVM	Linear	*Ward*	Poly		

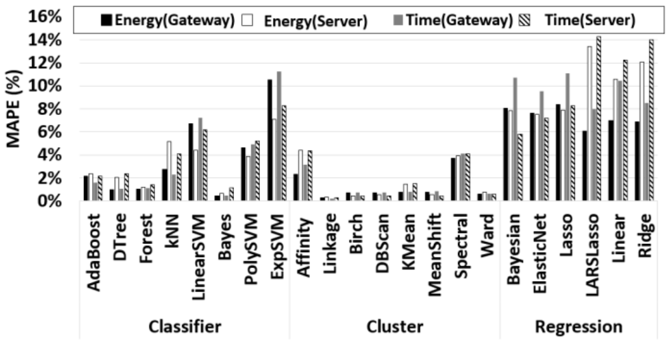


Figure 6. Accuracy Evaluation of Processing Models Constructed by CrossTest

accurately identify the linear relationship. The total runtime overhead of the characterization was 38 minutes on average for each ML algorithm. Since the offline characterization happens only only once for each ML algorithm, the overhead is negligible for runtime decisions.

B. Evaluation of Selective Models

As discussed in Section III.C, the proposed CrossTest automatically selects the best regression model among the model candidates. Table 3 shows the selected regression methodologies for the evaluated 22 ML algorithms. Even though we also verify log- and exponential-based regression models, all selected ones are linear and polynomial methods. As compared with the computation complexities of the algorithms, we can identify accurate regression methodologies without a priori knowledge. For example, it selects a linear model for the *linear regression* algorithm, whose complexity is $O(n)$, and a polynomial model for the *Lasso regression* algorithm which repeats the *Linear regression* algorithm internally to enhance the regression accuracy.

Figure 6 summarizes the accuracy of the selected processing models for each algorithm based on the cross validation. The accuracy is evaluated using Mean Absolute Percentage Error (MAPE). The results show that the constructed models accurately estimate the resource requirements of the two target devices. For example, we can estimate the execution time and energy consumption of the *Gateway* with average errors of 3.8% and 4.5%, respectively.

For the *Server*, the errors are 4.5% and 4.8%. The estimation errors of regression algorithms are relatively high compared to other algorithms. It is because the energy and execution times of the regression algorithms are much smaller than others, and thus the measurement noise highly influences the estimation accuracy. However, even for these cases, the models can estimate the requirements with less than error of 15%.

C. Task Allocation Optimizaion

The constructed models can be used for diverse optimization problems of IoT ecosystems. To show the practical value, in this evaluation, we address task allocation problems for a typical situation in IoT: whether the *Gateway* which collects raw sensory data should need to transfer the data to the *Server* for cloud computing, or process them locally without the network communication. In the scenarios, we consider two key factors which affect the resource usage: i) the data size, *s*, of the processing models and ii) the network bandwidth, *BW*, of the network models. We explore the feasibility for a wide range of data sizes from 50 Kbytes to 1 Gbytes.

Scenario 1: Performance-aware optimization in challenging network condition. Many IoT applications such as healthcare are expected to guarantee a quick response. A server platform can execute most ML algorithms much faster than a resource-constrained gateway. However, the data communication from the gateway to the cloud may require a long delay if the network bandwidth is limited. In this scenario, we estimate the performance of an ML algorithm execution by considering the application execution time and network bandwidth as follows:

$$t^{\alpha}_{Gateway}(s) \geq t^{\alpha}_{Server}(s) + \frac{s}{\mathrm{BW}}. \tag{1}$$

If the statement is true, we need to allocate the task in the cloud. Otherwise, we could execute them locally in the *Gateway* for better resource usage. In the evaluation of this scenario, we assume a constrained bandwidth range from 0.1 Mbps to 1 Mbps, which is compatible to the upload bandwidth of 3G network technology in US [18].

Figure 7a and 7b illustrate the performance-aware optimization of the *random forest* algorithm for two bandwidths. As shown in Figure 7a, there is a clear range of data sizes which the *Gateway* can perform the algorithm faster than the *Server*. For example, for the data sizes of less than 700 Mbytes, the *Gateway* is the better place to execute the algorithm. In addition, this decision point for the data sizes is changed depending on the available network bandwidth. For example, the suitable data size decreases with better network condition.

Scenario 2: Energy-aware optimization for resource-constrained device. Many IoT devices are resource-constrained. For example, gateways would use batteries as their main power source. In addition, they may harvest energy from environment. Thus, if network communication energy is higher than processing energy for delay-tolerant applications, it would be allowed to execute them on the *Gateway*. In this scenario, we compare energy consumption of network communication to processing energy in the resource-constrained device:

$$e^{\alpha}_{Gateway}(s) \geq N^{Type}(\mathrm{BW}) \times \frac{s}{\mathrm{BW}}. \tag{2}$$

Note that we have two different communication power models for Ethernet and WiFi, i.e., $N^{ETH}(\mathrm{BW})$ and $N^{WIFI}(\mathrm{BW})$. We assume the bandwidth range from 10 Mbps to 100Mbps, which is the full available range of the wired connection.

Figure 7c shows an illustration of this decision scenario for the *LARS Lasso* regression. The result shows that the algorithm should be executed on the *Gateway* even for enough network bandwidths and a large data size, e.g., 800 MBtyes with Ethernet communication. We have observed similar trends for other regression algorithms, since the execution times are significantly less than classification and clustering algorithms.

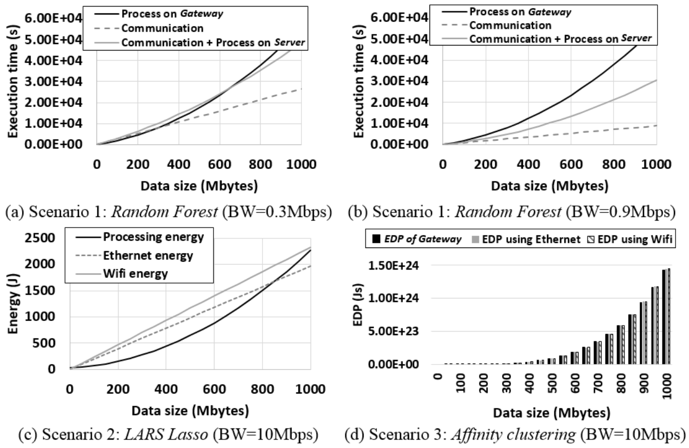
Scenario 3: EDP-aware optimization in IoT ecosystems. In this scenario, we use a metric, EDP (Energy-Delay Product) to compare the total computation cost between the gateway-based and the server-based processing. For some optimization problems, we may need to consider resource usage of the whole IoT ecosystems. For example, if we utilize the resource of a gateway by running an application on the edge device, a server could exploit its unused resource to run other tasks. The quantification of the entire resource usage is an open research problem. Here, we simplify this consideration and compare the EDP of the gateway-based processing to that of the communication cost and the server-based processing:

$$\begin{gathered} e^{\alpha}_{Gateway}(s) * t^{\alpha}_{Gateway}(s) \geq \\ N^{Type}(\mathrm{BW}) \times \left(\frac{s}{\mathrm{BW}}\right)^2 + e^{\alpha}_{Server}(s) \times t^{\alpha}_{Server}(s). \end{gathered} \tag{3}$$

For this scenario, we assume the full bandwidth range from 10 Mbps to 100Mbps.

Figure 7d presents the *affinity clustering* case which considers the EDP metric. The result shows that the local processing on the *Gateway* utilizes a similar amount of EDP to the *Server*-based processing. We have also observed other algorithms which show the compatible amount of EDP for the two different systems.

Figure 8 summarizes the results of all the 22 data processing applications for the three task allocation scenarios. We evaluate how many algorithms are decided to be processed on the *Gateway* instead of using the *Server* in cloud. We examine four different combinations of the data sizes and the bandwidth ranges assumed for each scenario. The results show that, for many cases, the *Gateway* can process the data more efficiently than the *Server*. For example, in Scenario 1, half of data processing applications can be executed on the *Gateway* to improve performance in a constrained bandwidth condition of 0.1 Mbps. Thus, in many IoT applications with unreliable network connectivity, the local processing would be a viable solution to address the performance issue. For Scenario 2, 27% of algorithms can be executed on the *Gateway* with better energy efficiency for the bandwidth of 1 Mbps. This means that, if an application is delay-tolerant, the *Gateway* can execute it locally to save energy by avoiding additional network communication. For Scenario 3, the *Gateway* can achieve better EDP for 55% algorithms with the maximum bandwidth of 10 Mbps. To conclude, for all considered metrics of each scenario, we observed high feasibility of edge/fog computing which processes data in the place close to where the IoT data are produced.



(a) Scenario 1: *Random Forest* (BW=0.3Mbps) (b) Scenario 1: *Random Forest* (BW=0.9Mbps)

(c) Scenario 2: *LARS Lasso* (BW=10Mbps) (d) Scenario 3: *Affinity clustering* (BW=10Mbps)

Figure 7. Examples of Task Allocation of Three Scenarios

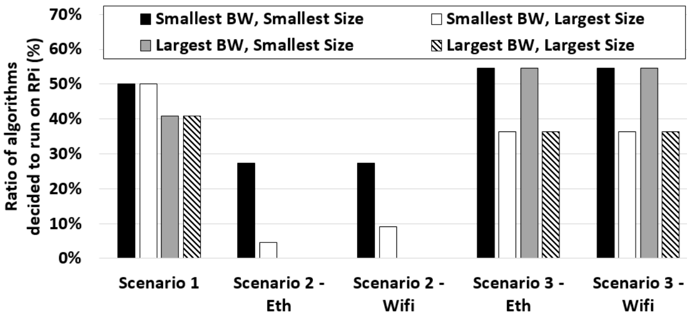


Figure 8. Summary of Application Fraction Decided to be Executed on *Gateway*

V. CONCLUSION

In this paper, we proposed a data processing application characterization framework, called CrossTest, which examines the future resource requirement of heterogeneous devices for IoT ecosystems. The CrossTest automatically builds energy and performance models of different data processing applications which perform popular machine learnings. The models are statistically and automatically built with consideration of under- and overfitting issues to accurately handle a large amount of data in Big Data domain. In our evaluation, we show that the proposed models can accurately estimate the requirements on average with less than 4.8% of error for the heterogeneous computing systems. We also show that, for more than 50% of data processing applications, IoT systems can achieve higher energy and performance efficiency by allocating the tasks on resource constrained devices rather than the centralized cloud. Our current work can be extended in many directions. For example, the characterization of other types of complex algorithms and data processing algorithms such as neural networks and compression procedures are considered as a part of our future work. In addition, we also plan to investigate IoT data processing on more various computing architectures such as GPGPU.

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